Time dependent multivariate distributions for piecewise-deterministic models of gene networks

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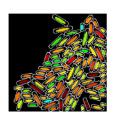
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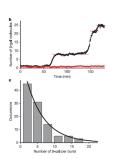




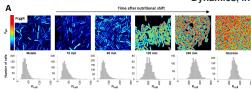
Stochastic gene expression



Heterogeneity of clone cells populations

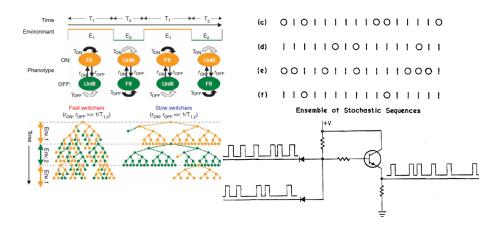


Dynamics, individual cell



Dynamics of stochastic gene expression, population

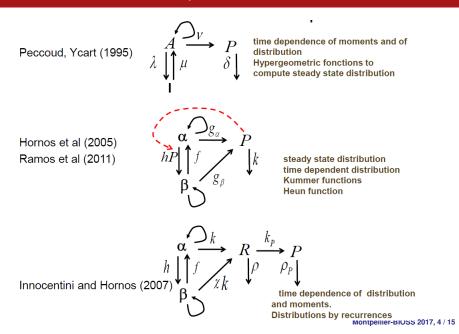
Applications



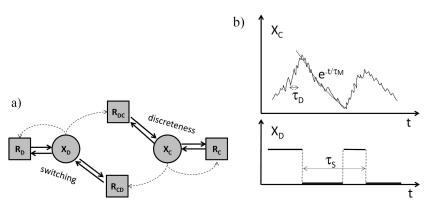
Adaptation of heterogeneous populations: stochastic switching

Gaines/Poppelbaum stochastic computing

Markovian models of stochastic promoters

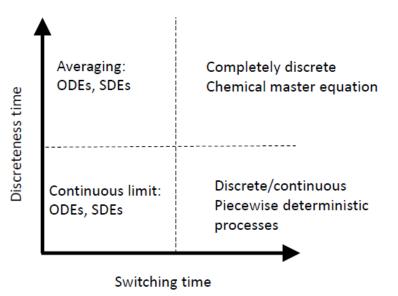


Multi-scaleness of stochastic gene expression

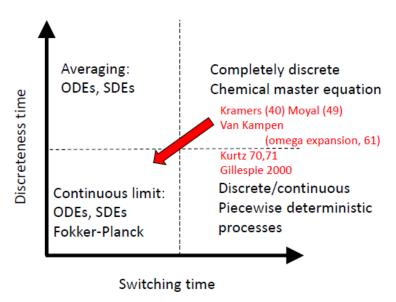


Switching and discreteness timescales (a) The partition of species and of the reactions; dotted lines mean that reaction rates depend on the corresponding species. (b) Typical trajectories of continuous and discrete variables: switched processes.

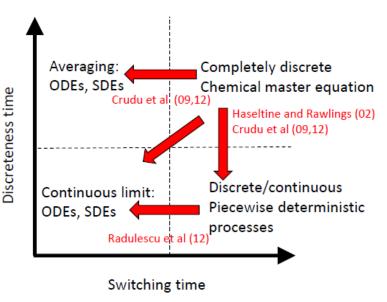
Continuous and hybrid approximations



Continuous and hybrid approximations



Continuous and hybrid approximations



Partial omega expansion

 Ω : size variable, $x_c = X_c/\Omega$.

$$\begin{split} \frac{\partial p}{\partial t}(X_D, x_c, X, t) &= \sum_{i \in \mathscr{R}_D \cup \mathscr{R}_{DC}} \left[V_i(X_D - \gamma_i^D, x_c; \mu) p(X_D - \gamma_i^D, x_c, t) - V_i(X; \mu) p(X_D, x_c, t) \right] + \\ &+ \sum_{i \in \mathscr{R}_C \cup \mathscr{R}_{CD}} \Omega \left[v_i(X_D, x_c - \gamma_i^C/\Omega; \mu) p(X_D, x_c - \gamma_i^C/\Omega, t) - v_i(X; \mu) p(X_D, x_c, t) \right] \end{split}$$

Master equation

$$\begin{array}{lcl} \frac{\partial \rho}{\partial t}(X_D,x_c,t) & = & -\frac{\partial [\Phi(X_D,x_c;\mu)\rho(X_D,x_c,t)]}{\partial x_c} + \sum_{i\in\mathscr{R}_D\cup\mathscr{R}_{DC}} [V_i(X_D-\gamma_i^D,x_c;\mu)\rho(X_D-\gamma_i^D,x_c,t) - \\ & - & V_i(X_D,x_c;\mu)\rho(X_D,x_c,t)], \text{where} \\ \Phi(X_D,x_c;\mu) & = & \sum_{i\in\mathscr{R}_D\cup\mathscr{R}_{DC}} \gamma_i^C v_i(X_D,x_c;\mu) \end{array}$$

Liouville-master equation

Single gene ON/OFF promoter: chemical master equation

$$\begin{array}{ccc}
\alpha & & & \\
h & & & \\
\downarrow & f & & \\
\beta & & & \\
\end{array}$$

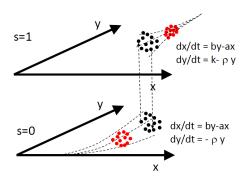
$$\begin{array}{ccc}
R & \xrightarrow{b} P \\
\downarrow \rho & a \\
\downarrow \\
\end{array}$$

X:P, Y:R.

$$\frac{\partial p}{\partial t}(1,X,Y,t) = k\Omega(p(1,X,Y-1,t)-p(1,X,Y,t)) + \\
+ p((Y+1)p(1,X,Y+1,t)-Yp(1,X,Y,t)) + bY(p(1,X-1,Y,t)-p(1,X,Y,t)) + \\
+ a((X+1)p(1,X+1,Y,t)-Xp(1,X,Y,t)) + fp(0,X,Y,t) - hp(1,X,Y,t)$$

$$\frac{\partial p}{\partial t}(0,X,Y,t) = p((Y+1)p(0,X,Y+1,t)-Yp(0,X,Y,t)) + bY(p(0,X-1,Y,t)-p(0,X,Y,t)) + \\
+ a((X+1)p(0,X+1,Y,t)-Xp(0,X,Y,t)) + hp(1,X,Y,t) - fp(0,X,Y,t)$$

Single gene ON/OFF promoter: Liouville-master equation



$$\frac{\partial p}{\partial t}(1,x,t) = -\frac{\partial [(by-ax)p(1,x,y,t)]}{\partial x} - \frac{\partial [(k-py)p(1,x,y,t)]}{\partial y} + fp(0,x,y,t) - hp(1,x,y,t)$$

$$\frac{\partial p}{\partial t}(0,x,y,t) = -\frac{\partial [(by-ax)p(0,x,y,t)]}{\partial x} - \frac{\partial [-pyp(0,x,y,t)]}{\partial y} + hp(1,x,y,t) - fp(0,x,y,t)$$

 $x: X/\Omega, y: Y/\Omega.$

Single gene ON/OFF promoter: Monte-Carlo

- (1) Set $s = s^{(0)}$, $x = x^{(0)}$, $y = y^{(0)}$, $t = t_0$, i = 0.
- (2) Generate $u \sim \mathcal{U}[0,1]$,
- (3) Integrate the system of ODEs

$$\begin{cases} \frac{dx}{dt} = by - ax \\ \frac{dy}{dt} = k\delta_{s,1} - \rho y, \\ \frac{dF}{dt} = -(f+h)F, \\ x(t_i) = x^{(i)}, y(t_i) = y^{(i)}, F(t_i) = 1, \end{cases}$$

between t_i and $t_i + \tau_i$ with the stopping condition $F(t_i + \tau_i) = u$.

- (4) Generate $v \sim \mathcal{U}[0,1]$ use it to pick $s^{(i+1)}$. (the decision is made in the same way as in the Gillespie algorithm).
- (5) Change the system state $(s^{(i)}, x, y)$ to $(s^{(i+1)}, x, y)$, and the time t_i to $t_{i+1} = t_i + \tau_i$.
- (6) Reiterate the system from 2) with the new state until a time t_{max} previously defined is reached.

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Single gene ON/OFF promoter: push forward

- (1) Consider fixed partition $t_0 = 0, t_1, ..., t_N = T$ fine enough such that s is constant on most subintervals.
- (2) For each possible instance s_0, s_1, \dots, s_{N-1} compute its probability

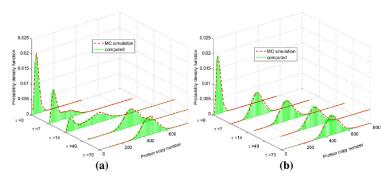
$$\mathbb{P}[s_0, \dots, s_{N-1}] = \sum_{s_0, \dots, s_{N-1}} \mathbb{P}[s_0] \, \mathbb{P}[s_1 | s_0] \dots \mathbb{P}[s_{N-1} | s_{N-2}]$$

where
$$\mathbb{P}[s_{k+1}|s_k]$$
 is the exact solution of $\frac{dp_0}{dt} = -tp_0 + h(1-p_0), \quad p_1 = 1-p_0.$

- (3) Compute x(t) and y(t) as exact solutions of $\frac{dx}{dt} = by ax$, $\frac{dy}{dt} = k\delta_{s,1} \rho y$
- (4) Gather all x(t), y(t) leading to the same distribution bin in (x, y) plane and sum the probabilities.

NB: we use the exact distribution of s to obtain the one of x, y. Possible to use the exact distribution of (s, y) to obtain the one of x

Single gene ON/OFF promoter: illustration of the methods



Dynamical evolution of protein probability density for slow switch $(\epsilon = (h+f)/\rho = 0.1)$ in a) and fast switch $(\epsilon = 5)$ in b).

Innocentini et al, Bull Math Biol (2016) 78:110-131.

Gene networks: work in progress

- The methods can be applied to any combination of promoters with or without feed-back.
- Limitations imposed by the number of distinct genes N_g.
- Push-forward is better than solving the 2^{Ng} Liouville-master PDEs.
- ▶ Push-forward is better than Monte-Carlo for small to medium N_g (circuits).